



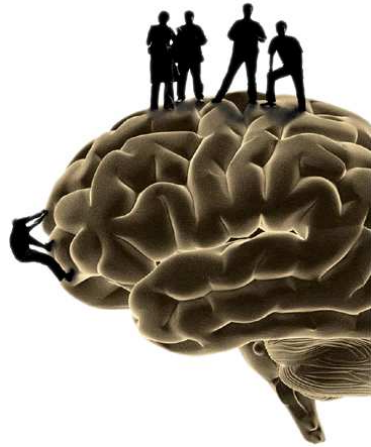
Methods for scaling neural computation

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Brains make sophisticated decisions given noisy and complex perceptual information.

To do so they leverage:

- an advanced integration of information across brain areas,
- and exquisite adaptation.



In past work, we've built large-integrated systems to reproduce several aspects of human cognition [Eliasmith et al, 2012].

Semantic Pointer Architecture Unified Network (SPAUN), is the current state-of-the-art in large-scale functional brain models.

- 8 tasks, 2.5M neurons, no changes to the model across any tasks.

SPAUN - list memorization

A 3 ► 0 1 5 8 7 3 ► ?

Show SPAUN movie.

SPAUN - rule inference

1	11	111
4	44	444
5	55	?

Show SPAUN movie.

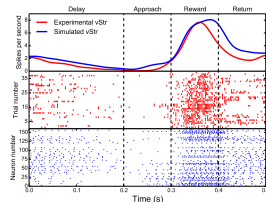
- Processing natural stimuli
 - human accuracy: 98%
 - model accuracy: 94%



- Cognitive problem solving (rule inference)
 - human accuracy: 89%
 - model accuracy: 88%

1	2	3
2	3	4
3	4	?

- Simple RL to update behaviour based on reward

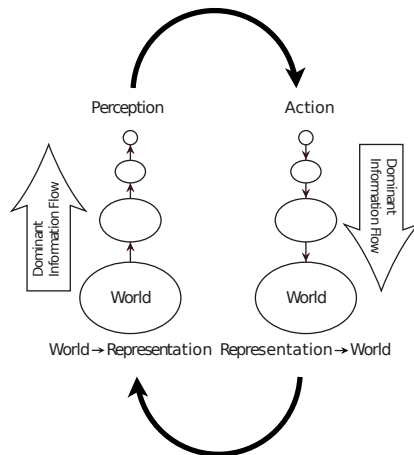


Extending SPAUN

- Implementing more sophisticated cortical circuits
 - Nonlinear adaptation
- Extending subcortical adaptive decision making
 - Hierarchical reinforcement learning

Action and perception

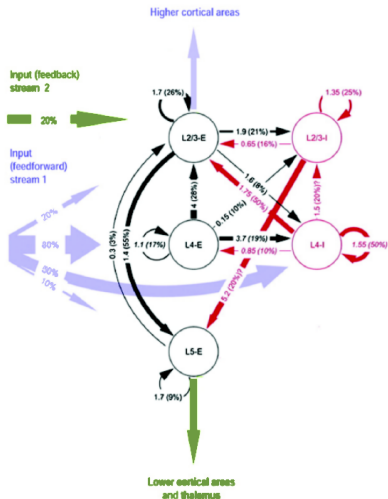
The dual of the control problem is the prediction problem.



Show quadcopter video.

A canonical microcircuit

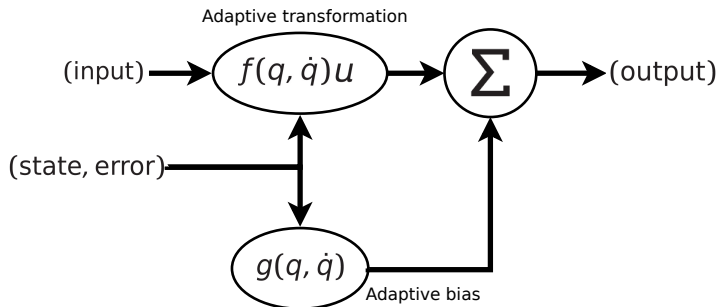
Haeusler and Maass (2007)



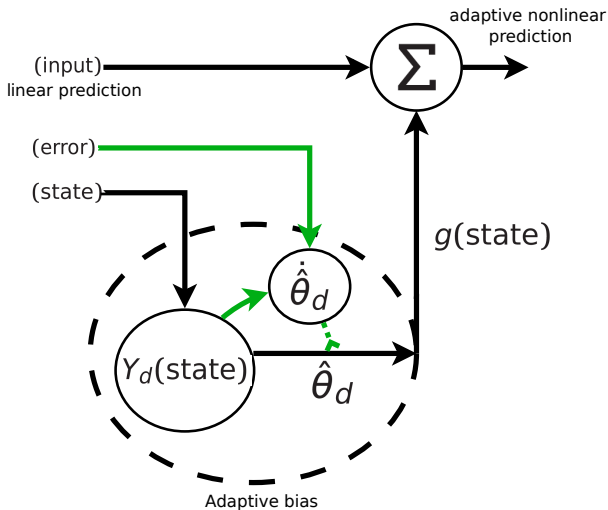
Adaptive nonlinear circuits

Slotine has developed an extremely effective high-speed nonlinear adaptive algorithm [Cheah et al, 2006, Sanner and Slotine, 1992].

Two types of adaptation occur in these circuits:



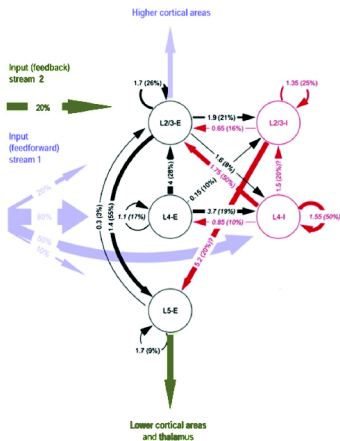
Adaptive nonlinear circuits



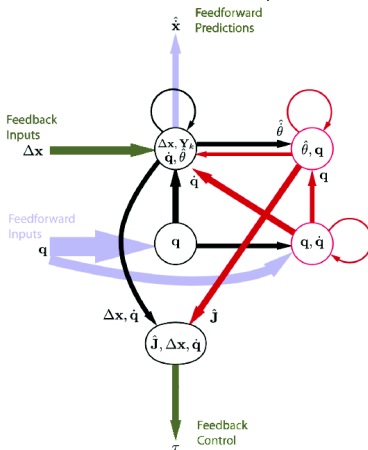
A canonical microcircuit

The nonlinear adaptation circuit maps on to the microcircuit seen throughout the cortex.

Haeusler and Maass (2007)



Canonical microcircuit for nonlinear adaptive control



Adaptive action

A quadcopter being controlled by an adaptive nonlinear controller implemented in spiking neurons.

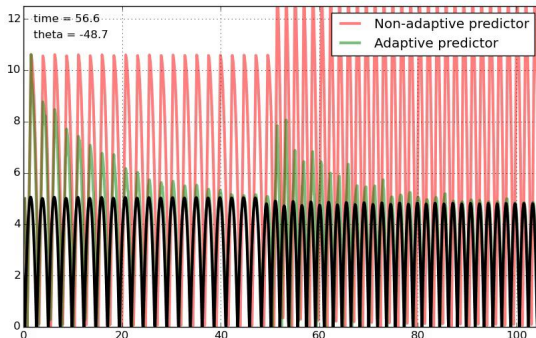
It learns online to account for the effects of gravity and wind.

Show video.

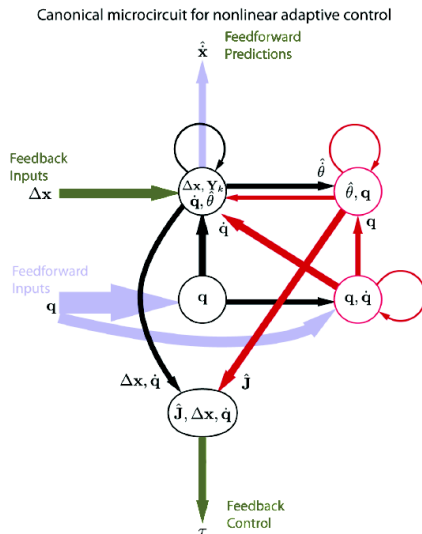
Adaptive perception

Here, the circuit learns to predict the path of a bouncing ball.

Show video.

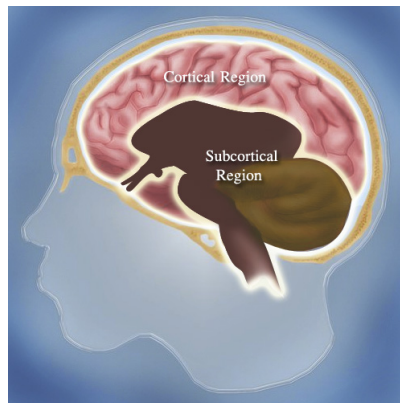


All examples done with the same circuit

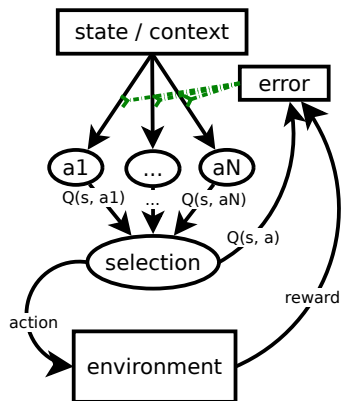


Two kinds of adaptation

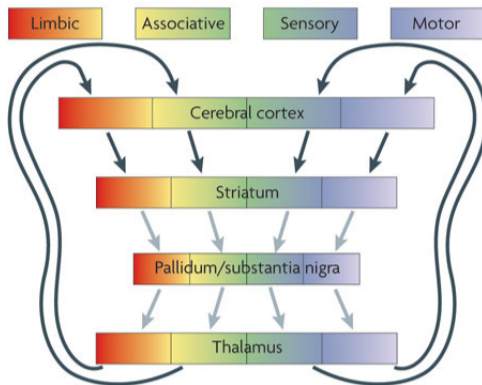
- Cortical adaptation
 - e.g. sensory/motor processing
- Subcortical adaptation
 - decision making given context/environment



Reinforcement learning

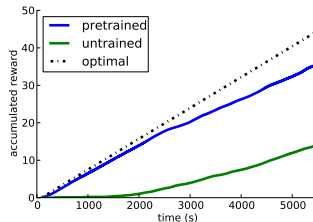
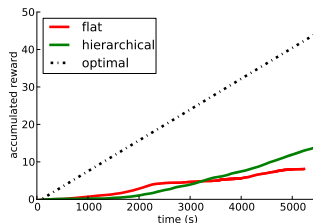
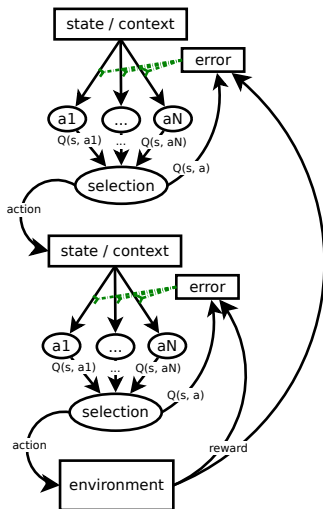


Cortico-basal ganglio-thalamic loop



Hierarchical reinforcement learning

First neural implementation of hierarchical reinforcement learning.





We believe that the strengths of each adaptation system will be most compellingly realized in an integrated model that takes advantage of learning and structure at both cortical and subcortical levels.

Tasks models are well-suited for

Strengths and weaknesses parallel those of mammalian brains.

Strengths:

- pattern identification
- nonlinear adaptive perception and action
- parallel processing

Weaknesses:

- precise numerical calculation
- rapid serial information processing

